

# New perspectives on probabilistic methods for nonlinear transient dynamics in civil engineering

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New perspectives on probabilistic methods  
for nonlinear transient **dynamics in civil engineering**

# Structural dynamics in civil engineering

Dynamics = study of body motion under forces

Equation of motion  $\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} = \mathbf{f}(t)$

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inertial forces      damping forces      restoring forces

Structure



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inertial forces      damping forces      restoring forces      external forces

Structure



External forces      wind pressure, ground acceleration, wave, crowd

New perspectives on probabilistic methods  
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# Nonlinear behavior in civil engineering

Equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} = \mathbf{f}(t)$$

\      /  
linear  
internal forces

# Nonlinear behavior in civil engineering

Equation of motion 
$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t)$$

$\backslash \quad / \quad \backslash$   
linear                  nonlinear  
internal forces      internal forces

## Nonlinear behavior in structures

- large displacement  $\mathbf{K}(\mathbf{y})$  :  $\mathbf{y}$  is large w.r.t. the static equilibrium
- material nonlinearities : plasticity, cracking
- damping devices : nonlinear damping law  $\mathbf{C}(\dot{\mathbf{y}})$ , tuned liquid dampers



# Nonlinear behavior in civil engineering

Equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \underbrace{\mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y}}_{\text{linear internal forces}} + \underbrace{\mathbf{g}(\mathbf{y}, \dot{\mathbf{y}})}_{\text{nonlinear internal forces}} = \mathbf{f}(t)$$

## Nonlinear behavior in structures

- large displacement  $\mathbf{K}(\mathbf{y})$  :  $\mathbf{y}$  is large w.r.t. the static equilibrium
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## Sources of difficulties

- superposition principle is broken
- Fourier analysis and modal superposition cannot be applied

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# Uncertainty in civil engineering

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↳ a lack of knowledge → it is impossible to exactly describe future outcomes of an experiment

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## Methods

- Non-probabilistic : fuzzy arithmetics, random sets
- Probabilistic : based on the probability theory, the uncertainty can be *measured*

# Uncertainty in civil engineering

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## Sources of uncertainty

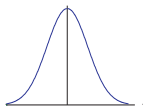
- Structure :  $\mathbf{M}(\theta)$ ,  $\mathbf{K}(\theta)$ ,  $\mathbf{C}(\theta)$  uncertain
- Excitation :  $\mathbf{f}(t, \theta)$  uncertain

## Notation

$(\cdot, \theta) \rightarrow$  function of the randomness in the universe (probability space)

# Uncertainty in civil engineering

Random excitations  $\mathbf{f}(t, \theta)$



Gaussian  
 $\Sigma_{\mathbf{f}} \mu_{\mathbf{f}}$



stationary



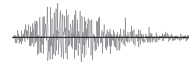
statistics time-independent



non-Gaussian  
 $\psi_{\mathbf{f}}$



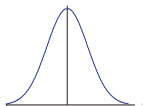
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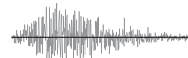
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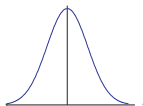
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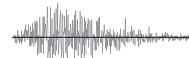
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## Spatial Coherence

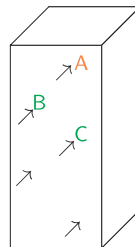
forces at different locations  
are not statistically independent

Wind blowing on building  
pressure A is correlated  
to pressures B, C,...

Coherence  
(frequency domain)



Correlation  
(time domain)





# Probabilistic Methods

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

How to solve the equation of motion ?

$\mathbf{f}$  is Gaussian and  $\mathbf{g} = \mathbf{0} \longrightarrow \mathbf{y}(t, \theta)$  is Gaussian

$\mathbf{f}$  is Gaussian and  $\mathbf{g} \neq \mathbf{0} \longrightarrow \mathbf{y}(t, \theta)$  is **non-Gaussian**

		FPK equation	MC simulation	Equ. Linearization
<b>Size</b>	small large			
<b>Transience</b>				
<b>Data</b>	variance pdf			

# Probabilistic Methods

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

How to solve the equation of motion ?

## Fokker-Planck Equation

$\psi(t)$  the probability density function of  $\mathbf{y}$  and  $\dot{\mathbf{y}}$

$$\frac{\partial \psi}{\partial t} + \sum_i \frac{\partial}{\partial x_i} (a_i \psi) = \sum_{i,j} \frac{\partial^2}{\partial x_i \partial x_j} (D_{ij} \psi)$$

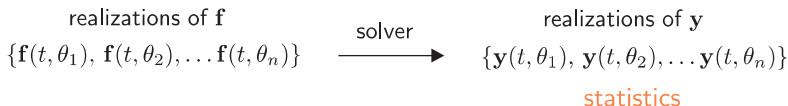
		FPK equation		
Size	small large	possible ! forget it !		
Transience		adapted		
Data	variance pdf	ideal		

# Probabilistic Methods

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

How to solve the equation of motion ?

## Monte Carlo simulation



		FPK equation	MC simulation	
Size	small large	possible ! forget it !	possible	
Transience		adapted	possible	
Data	variance pdf	ideal	possible	

# Probabilistic Methods

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

How to solve the equation of motion ?

## Equivalent Statistical Linearization

- Approximate method
- Nonlinear forces  $\mathbf{g}(\mathbf{y}, \dot{\mathbf{y}})$  are replaced by **Equivalent Linear** forces
- **Statistical Equivalence**  $\longrightarrow$  minimize the error on the **variance**

		FPK equation	MC simulation	Equ. Linearization
Size	small large	possible ! forget it !	possible	inappropriate ! pertinent !
Transience		adapted	possible	challenging
Data	variance pdf	ideal	possible	targeted ! too approximate !

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# Motivations

		FPK equation	MC simulation	Equ. Linearization
Size	small	possible !	possible	inappropriate !
	large	forget it !		pertinent !
Transience		adapted	possible	challenging
Data	variance	ideal	possible	targeted !
	pdf			too approximate !

*" I force myself to contradict myself in order*

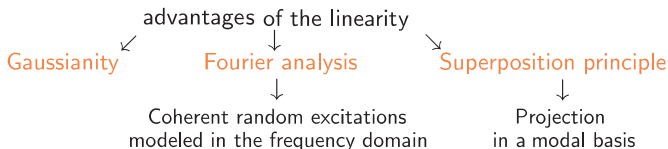
*to avoid conforming to my own taste "*

M. Duchamp

# Motivations : Equivalent statistical linearization

	FPK equation	MC simulation	Equ. Linearization
Size <small>small</small> <b>large</b>	possible ! forget it !	possible	inappropriate ! pertinent !
<b>Transience</b>	adapted	possible	<b>challenging</b>
Data <b>variance</b> pdf	ideal	possible	targeted ! too approximate !

Why ? Large structures + coherent random loads  $\rightarrow$  MC inefficient !



## Goal (Part I)

- Develop a method for linear transient analysis
- Extension for equivalent statistical linearization

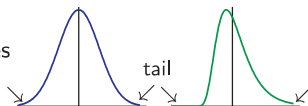
# Motivations : Fokker-Planck Equation

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Why ?

MC : slow convergence in low probability zones

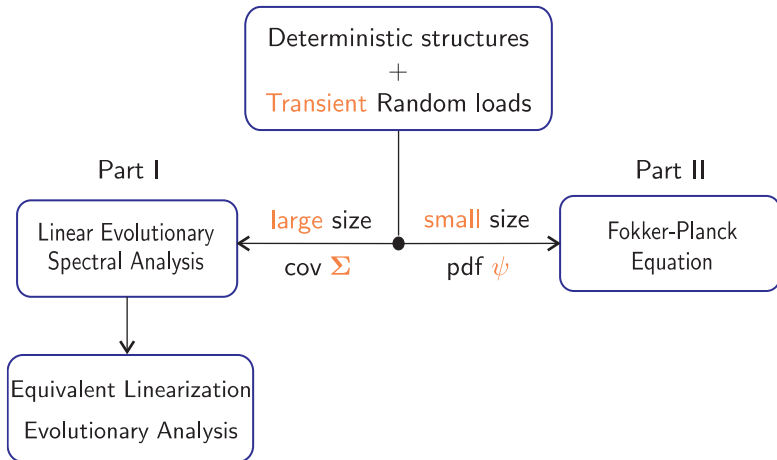
FPK : pdf  $\rightarrow$  tails of the distribution

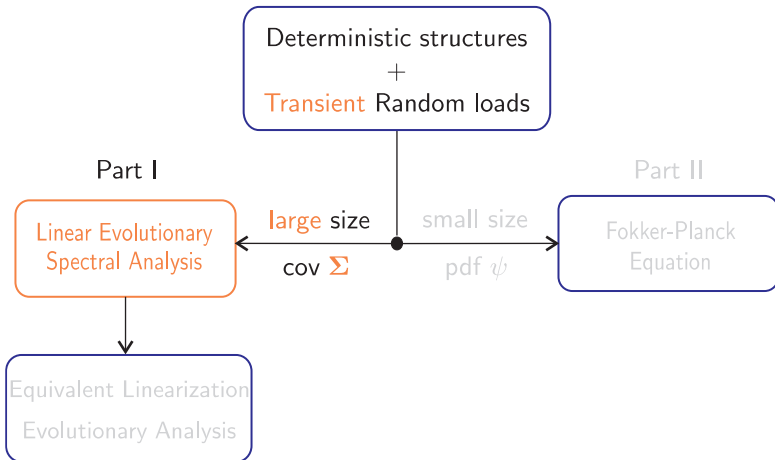


Goal (Part II)

Develop and apply an accurate numerical solver







## Stationary random processes

## Linear evolutionary spectral analysis

Stationary random processes

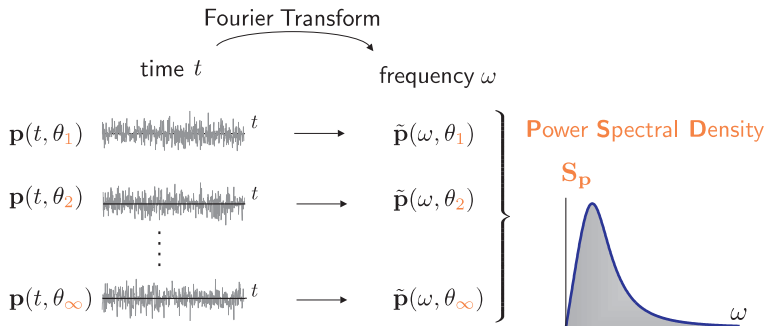
Evolutionary spectral analysis

Asymptotic expansion-based method

Efficient generalized procedure

# Spectral representation of stationary random processes

## Fourier analysis and random vectors



## Properties

Covariance  $\rightarrow \Sigma_p = \int_{\mathbb{R}} S_p d\omega$

$p$  coherent  $\rightarrow S_p$  is full

# Stationary spectral analysis and modal projection

Equation of motion in basis  $\Phi$

$$\begin{array}{ccc}
 \mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{f}(t, \theta) & \longrightarrow & \mathbf{K}\Phi = \omega^2 \mathbf{M}\Phi \\
 & & \downarrow \text{Eigenvalue problem} \\
 \ddot{\mathbf{q}} + \mathbf{D}\dot{\mathbf{q}} + \mathbf{\Omega}\mathbf{q} = \mathbf{p}(t, \theta) & \longleftarrow & \underset{\text{nodal}}{\mathbf{x}} = \underset{\text{modal}}{\Phi}\mathbf{q} \quad \text{size } \mathbf{q} \ll \text{size } \mathbf{x}
 \end{array}$$

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 \end{array}$$

Transfer Function  
in modal basis

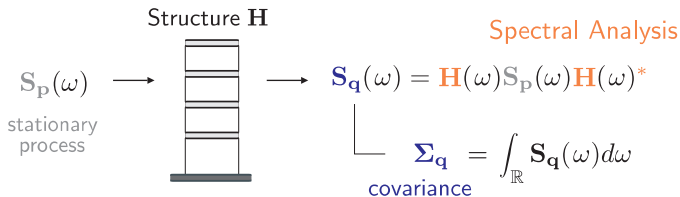
$$\mathbf{H}(\omega) = (\mathbf{\Omega} - \omega^2 \mathbf{I} + i\omega \mathbf{D})^{-1}$$

# Stationary spectral analysis and modal projection

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 \end{array}$$

Transfer Function in modal basis  $\mathbf{H}(\omega) = (\mathbf{\Omega} - \omega^2 \mathbf{I} + i\omega \mathbf{D})^{-1}$



## Linear evolutionary spectral analysis

Stationary random processes

**Evolutionary spectral analysis**

Asymptotic expansion-based method

Efficient generalized procedure



# Evolutionary random processes

How is built an evolutionary process ?

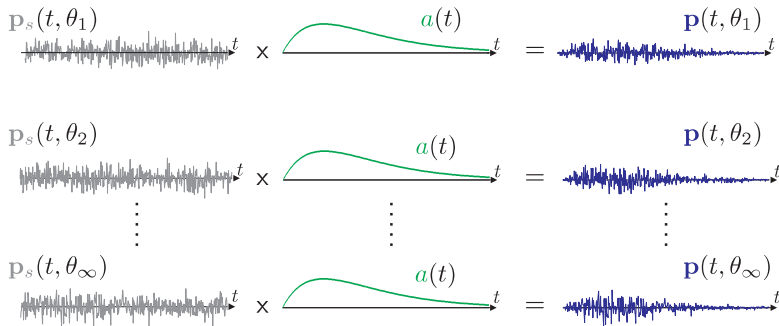
Stationary  
random process

$\times$

Deterministic  
time window

$=$

Evolutionary  
random process

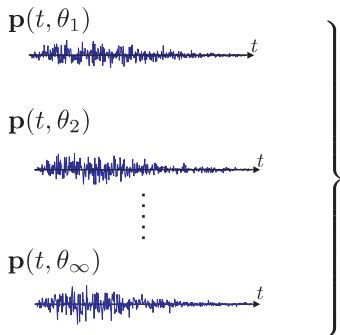


# Evolutionary random processes

Evolutionary process

$$\mathbf{p}(t, \theta) = \underbrace{a(t)}_{\substack{\text{time} \\ \text{window}}} \mathbf{p}_s(t, \theta)$$

stationary process



Extended Fourier Representation

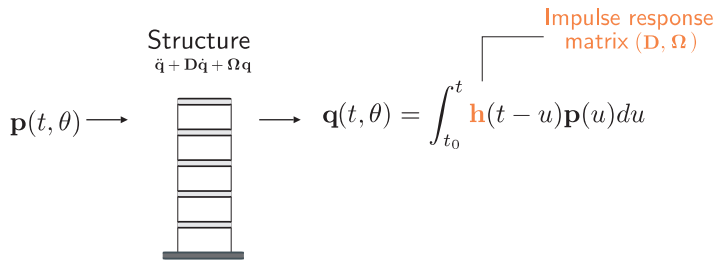
$$\mathbf{p}(t) = \int_{\mathbb{R}} a(t, \omega) e^{i\omega t} d\tilde{\mathbf{p}}(\omega)$$

Evolutionary Power Spectral Density

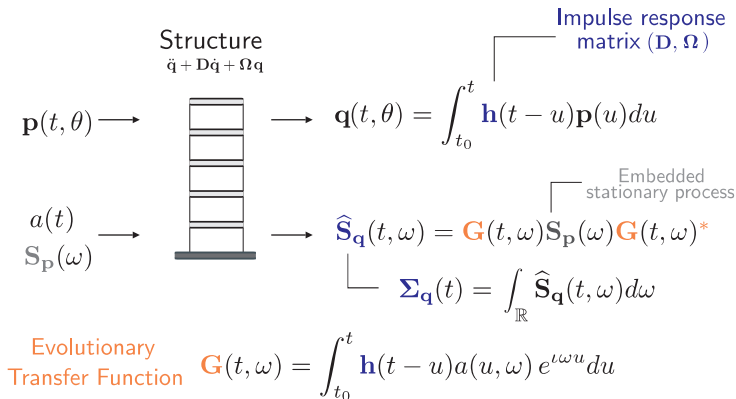
$$\hat{\mathbf{S}}_{\mathbf{p}}(t, \omega) = |a(t, \omega)|^2 \underbrace{\mathbf{S}_{\mathbf{p}}(\omega)}_{\substack{\text{Embedded} \\ \text{stationary process}}}$$

$$\Sigma_{\mathbf{p}}(t) = \int_{\mathbb{R}} \hat{\mathbf{S}}_{\mathbf{p}}(t, \omega) d\omega$$

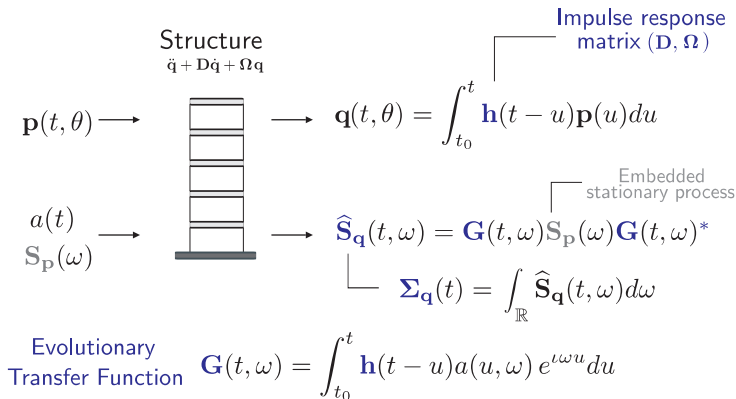
# Evolutionary spectral analysis



# Evolutionary spectral analysis



# Evolutionary spectral analysis



How to *efficiently* compute  $\mathbf{h}(t)$  and  $\mathbf{G}(t, \omega)$  ?

## Linear evolutionary spectral analysis

Stationary random processes

Evolutionary spectral analysis

**Asymptotic expansion-based method**

Efficient generalized procedure

# How to compute $\mathbf{h}(t)$ ?

$$\mathbf{h}(t) = \int_{\mathbb{R}} \mathbf{H}(\omega) e^{i\omega t} d\omega$$

Impulse response matrix = Inverse Fourier Transform of the transfer matrix

Decoupled modes :  $\mathbf{\Omega}_d$ ,  $\mathbf{D}_d$  diagonal

$$\mathbf{H}_d(\omega) = (\mathbf{\Omega}_d - \omega^2 \mathbf{I} + i\omega \mathbf{D}_d)^{-1} \xrightarrow{\text{EASY}} (\mathbf{h}_d(t))_i = \frac{e^{\Omega_i^+ t} - e^{\Omega_i^- t}}{2i\omega_i \sqrt{1 - \xi_i^2}}$$

closed form expressions

closed form expressions

# How to compute $\mathbf{h}(t)$ ?

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closed form expressions                      closed form expressions

Mechanically Coupled modes :  $\Omega, \mathbf{D}$  non-diagonal

$$\mathbf{H}(\omega) = (\Omega - \omega^2 \mathbf{I} + i\omega \mathbf{D})^{-1} \xrightarrow{?} \text{NO closed form expression}$$



## How to compute $\mathbf{h}(t)$ ?

$$\mathbf{h}(t) = \int_{\mathbb{R}} \mathbf{H}(\omega) e^{\iota\omega t} d\omega$$

$\downarrow$

$$\mathbf{H} = \left( \underbrace{\boldsymbol{\Omega} - \omega^2 \mathbf{I} + \iota\omega \mathbf{D}}_{\mathbf{J}} \right)^{-1}$$

# How to compute $\mathbf{h}(t)$ ?

$$\begin{aligned}
 \mathbf{h}(t) &= \int_{\mathbb{R}} \mathbf{H}(\omega) e^{i\omega t} d\omega \\
 &\downarrow \\
 \mathbf{H} &= \left( \underbrace{\boldsymbol{\Omega} - \omega^2 \mathbf{I} + i\omega \mathbf{D}}_{\mathbf{J}} \right)^{-1} \\
 &\quad \left( \begin{array}{ccc} \square & \square & \square \\ \square & \square & \square \\ \square & \square & \square \end{array} \right) = \left( \begin{array}{ccc} \square & & \\ & \square & \\ & & \square \end{array} \right) + \left( \begin{array}{ccc} & \square & \square \\ \square & & \square \\ \square & \square & \square \end{array} \right) \\
 &\quad \begin{array}{cc} \mathbf{J}_d & \mathbf{J}_o \\ \text{Decoupled} & \text{Coupling} \\ & \text{small} \end{array} \\
 &\quad \downarrow \\
 &\quad \mathbf{H}_d = \mathbf{J}_d^{-1}
 \end{aligned}$$

# How to compute $\mathbf{h}(t)$ ?

$$\mathbf{h}(t) = \int_{\mathbb{R}} \mathbf{H}(\omega) e^{i\omega t} d\omega$$



$$\mathbf{H} = \left( \underbrace{\boldsymbol{\Omega} - \omega^2 \mathbf{I} + i\omega \mathbf{D}} \right)^{-1}$$

$\mathbf{J}$

$$\begin{pmatrix} \square & \square & \square \\ \square & \square & \square \\ \square & \square & \square \end{pmatrix} = \begin{pmatrix} \square & & \\ & \square & \\ & & \square \end{pmatrix} + \begin{pmatrix} & \square & \square \\ \square & & \square \\ \square & \square & \square \end{pmatrix}$$

Decoupled

Coupling  
*small*



$$\mathbf{H}_d = \mathbf{J}_d^{-1}$$



$$\boxed{\mathbf{H} = (\mathbf{I} + \mathbf{H}_d \mathbf{J}_o)^{-1} \mathbf{H}_d}$$

# Asymptotic Expansion-based Method

$$(\mathbf{I} + \mathbf{H}_d \mathbf{J}_o)^{-1}$$

↓

?

$$\frac{1}{1 + \varepsilon}$$

↓  $\varepsilon < 1$

$$\frac{1}{1 + \varepsilon} = 1 - \varepsilon + \dots$$

# Asymptotic Expansion-based Method

$$(\mathbf{I} + \mathbf{H}_d \mathbf{J}_o)^{-1}$$

$$\downarrow \rho_{\mathbf{J}} < 1$$

$$\mathbf{I} + \sum_{k=1}^{\infty} (-1)^k \underbrace{(\mathbf{H}_d \mathbf{J}_o)^k}_{\text{closed form}}$$

$$\frac{1}{1 + \varepsilon}$$

$$\downarrow \varepsilon < 1$$

$$\frac{1}{1 + \varepsilon} = 1 - \varepsilon + \dots$$

## Convergence criterion

$\rho_{\mathbf{J}}$  = maximum eigenvalue of  $\mathbf{H}_d \mathbf{J}_o$  over all  $\omega$  (in norm)

# Asymptotic Expansion-based Method

$$\mathbf{H} = (\mathbf{I} + \mathbf{H}_d \mathbf{J}_o)^{-1} \mathbf{H}_d$$

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## Convergence criterion

$\rho_{\mathbf{J}}$  = maximum eigenvalue of  $\mathbf{H}_d \mathbf{J}_o$  over all  $\omega$  (in norm)

## Asymptotic expansion + Cauchy's theorem

$$\int_{\mathbb{R}} \mathbf{H} e^{i\omega t} d\omega \quad \longrightarrow \quad \mathbf{h} = \mathbf{h}_d + \sum_{k=1}^{\infty} \Delta \mathbf{h}_k$$

decoupled system closed form correction terms

# Asymptotic Expansion-based Method

$$\mathbf{H} = (\mathbf{I} + \mathbf{H}_d \mathbf{J}_o)^{-1} \mathbf{H}_d$$

$$\downarrow \quad \rho_{\mathbf{J}} < 1$$

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$$\frac{1}{1 + \varepsilon}$$

$$\downarrow \quad \varepsilon < 1$$

$$\frac{1}{1 + \varepsilon} = 1 - \varepsilon + \dots$$

## Convergence criterion

$\rho_{\mathbf{J}}$  = maximum eigenvalue of  $\mathbf{H}_d \mathbf{J}_o$  over all  $\omega$  (in norm)

## Asymptotic expansion + Cauchy's theorem + Truncation

$$\int_{\mathbb{R}} \mathbf{H}_N e^{i\omega t} d\omega \quad \longrightarrow \quad \mathbf{h}_N = \mathbf{h}_d + \sum_{k=1}^N \Delta \mathbf{h}_k$$

decoupled system
closed form correction terms



# How to compute $\mathbf{G}(t, t_0, \omega)$ ?

$$\mathbf{G}(t, t_0, \omega) = \int_{t_0}^t \mathbf{h}(t-u)a(u)e^{i\omega u} du$$

# How to compute $\mathbf{G}(t, t_0, \omega)$ ?

$$\mathbf{G}_{\mathbf{N}}(t, t_0, \omega) = \int_{t_0}^t \mathbf{h}_{\mathbf{N}}(t - u) a(u) e^{i\omega u} du$$

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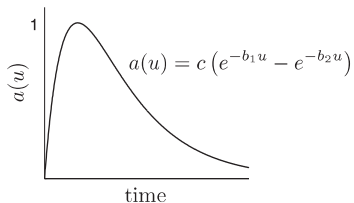
$a(u)$  is a tractable function



closed form expression  $\mathbf{G}_N$

DONE !

Shinozuka window



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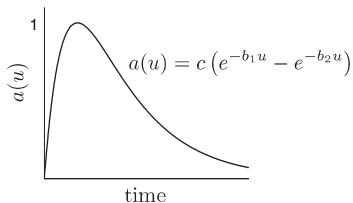
$a(u)$  is a tractable function



closed form expression  $\mathbf{G}_N$

**DONE !**

Shinozuka window

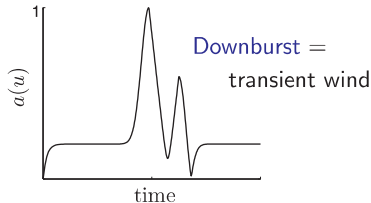


$a(u)$  known numerically



$\mathbf{G}_N$  **cannot** be computed  
from  $t_0$  to  $t$

Holmes window



## Linear evolutionary spectral analysis

Stationary random processes

Evolutionary spectral analysis

Asymptotic expansion-based method

Efficient generalized procedure

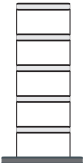
# Efficient procedure : state space formalism


State space formalism  $\mathbf{z}(t, \theta) = \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix}$

$$\mathbf{p}(t, \theta) \longrightarrow \text{stack of 6 boxes} \longrightarrow \mathbf{z}(t, \theta) = \int_{t_0}^t \overset{\text{state transition matrix}}{\Psi}(t, u) \begin{bmatrix} \mathbf{0} \\ \mathbf{p}(u) \end{bmatrix} du$$

# Efficient procedure : state space formalism

State space formalism  $\mathbf{z}(t, \theta) = \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix}$

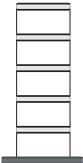
$\mathbf{p}(t, \theta) \longrightarrow$ 

 $\longrightarrow \mathbf{z}(t, \theta) = \int_{t_0}^t \overset{\text{state transition matrix}}{\Psi(t, u)} \begin{bmatrix} \mathbf{0} \\ \mathbf{p}(u) \end{bmatrix} du$

$a(t)$   
 $\mathbf{S}_p(\omega) \longrightarrow$ 

 $\longrightarrow \hat{\mathbf{S}}_z(t, \omega) = \Upsilon(t, \omega) \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_p \end{bmatrix} \Upsilon(t, \omega)^*$

Evolutionary state transfer matrix  $\Upsilon(t, t_0, \omega) = \int_{t_0}^t a(u, \omega) \Psi(t, u) \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} e^{i\omega u} du$

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Evolutionary state transfer matrix

$$\Upsilon(t, t_0, \omega) = \int_{t_0}^t a(u, \omega) \Psi(t, u) \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} e^{i\omega u} du$$

$$= \begin{bmatrix} \mathbf{0} & \mathbf{G}(t, t_0, \omega) \\ \mathbf{0} & \partial_t \mathbf{G}(t, t_0, \omega) \end{bmatrix}$$



# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

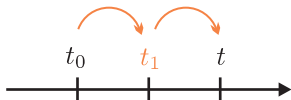
Semi-group property



$$\Psi(t, t_0) =$$

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

Semi-group property



$$\Psi(t, t_0) = \Psi(t, t_1)\Psi(t_1, t_0)$$

for LTI and LTV systems

LTI system = Linear Time Invariant

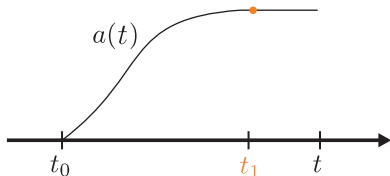
LTV system = Linear Time Variant

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

Semi-group property

$$\Psi(t, t_0) = \Psi(t, t_1) \Psi(t_1, t_0)$$

for LTI and LTV systems



Recurrence relation

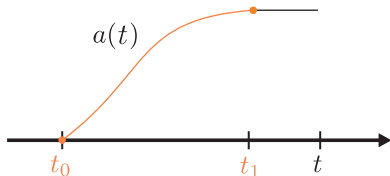
$$\Upsilon(t, t_0, \omega) = \Upsilon(t, t_1, \omega) + \Psi(t, t_1) \Upsilon(t_1, t_0, \omega)$$

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

Semi-group property

$$\Psi(t, t_0) = \Psi(t, t_1) \Psi(t_1, t_0)$$

for LTI and LTV systems



Recurrence relation

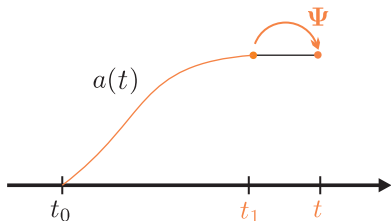
$$\Upsilon(t, t_0, \omega) = \Upsilon(t, t_1, \omega) + \underbrace{\Psi(t, t_1) \Upsilon(t_1, t_0, \omega)}_{\substack{\text{known} \\ t_0 \rightarrow t_1}}$$

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

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for LTI and LTV systems



Recurrence relation

$$\Upsilon(t, t_0, \omega) = \Upsilon(t, t_1, \omega) + \underbrace{\Psi(t, t_1)}_{\text{known } t_0 \rightarrow t_1} \underbrace{\Upsilon(t_1, t_0, \omega)}_{\text{known } t_0 \rightarrow t_1}$$

State transition  
 $t_1 \rightarrow t$

$\omega$  independent

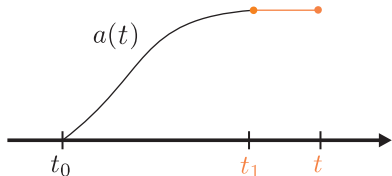
$a(t)$  independent

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

Semi-group property

$$\Psi(t, t_0) = \Psi(t, t_1) \Psi(t_1, t_0)$$

for LTI and LTV systems



Recurrence relation

$$\Upsilon(t, t_0, \omega) = \underbrace{\Upsilon(t, t_1, \omega)}_{\substack{\text{Convolution} \\ t_1 \rightarrow t}} + \underbrace{\Psi(t, t_1)}_{\substack{\text{State transition} \\ t_1 \rightarrow t}} \underbrace{\Upsilon(t_1, t_0, \omega)}_{\substack{\text{known} \\ t_0 \rightarrow t_1}}$$

$$\begin{bmatrix} 0 & \mathbf{G}(t, t_1, \omega) \\ 0 & \partial_t \mathbf{G}(t, t_1, \omega) \end{bmatrix}$$

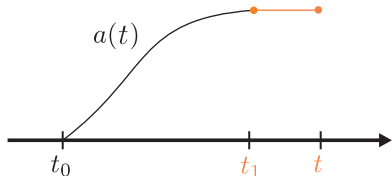
$\omega$  independent  
 $a(t)$  independent

# Efficient procedure : How to compute $\Upsilon(t, t_0, \omega)$ ?

Semi-group property

$$\Psi(t, t_0) = \Psi(t, t_1) \Psi(t_1, t_0)$$

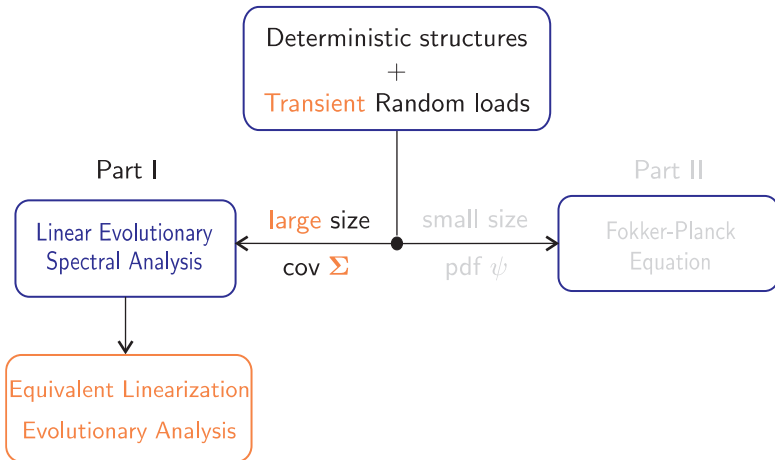
for LTI and LTV systems



Recurrence relation

$$\Upsilon_N(t, t_0, \omega) = \underbrace{\Upsilon_N(t, t_1, \omega)}_{\text{Convolution } t_1 \rightarrow t} + \underbrace{\Psi(t, t_1)}_{\text{State transition } t_1 \rightarrow t} \underbrace{\Upsilon_N(t_1, t_0, \omega)}_{\text{known } t_0 \rightarrow t_1}$$

Convolution  $t_1 \rightarrow t$   
 State transition  $t_1 \rightarrow t$   
 NO asymptotic approximation





## Equivalent linearization and evolutionary analysis

### Equivalent statistical linearization

Multiple scales approach

Application

# Equivalent linearization : basement

Nonlinear equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

$\mathbf{y}(t, \theta)$  is a **Non-Gaussian** process; covariance matrix  $\Sigma_{\mathbf{y}}$  ?

# Equivalent linearization : basement

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Gaussian Equivalent Linearization

$\mathbf{y}(t, \theta) \longrightarrow \mathbf{x}(t, \theta)$  is a Gaussian process

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} + \mathbf{C}_{eq}\dot{\mathbf{x}} + \mathbf{K}_{eq}\mathbf{x} = \mathbf{f}(t, \theta)$$

# Equivalent linearization : basement

## Nonlinear equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{f}(t, \theta)$$

$\mathbf{y}(t, \theta)$  is a Non-Gaussian process; covariance matrix  $\Sigma_{\mathbf{y}}$  ?

## Gaussian Equivalent Linearization

$\mathbf{y}(t, \theta) \longrightarrow \mathbf{x}(t, \theta)$  is a Gaussian process

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} + \mathbf{C}_{eq}\dot{\mathbf{x}} + \mathbf{K}_{eq}\mathbf{x} = \mathbf{f}(t, \theta)$$

How ?

minimize the error b/w  $\mathbf{g}(\mathbf{x}, \dot{\mathbf{x}})$  and  $\mathbf{C}_{eq}\dot{\mathbf{x}} + \mathbf{K}_{eq}\mathbf{x}$  in the mean squared sense

$$\mathbf{C}_{eq}(\Sigma_{\mathbf{x}}, \Sigma_{\dot{\mathbf{x}}}) \quad \mathbf{K}_{eq}(\Sigma_{\mathbf{x}}, \Sigma_{\dot{\mathbf{x}}})$$

Covariance matrices  $\Sigma_{\mathbf{x}}$  and  $\Sigma_{\dot{\mathbf{x}}}$  are UNKNOWN

# Equivalent linearization : example

## Gaussian Equivalent Linearization

$$\mathbf{M}\ddot{\mathbf{x}} + (\mathbf{C} + \mathbf{C}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\dot{\mathbf{x}} + (\mathbf{K} + \mathbf{K}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\mathbf{x} = \mathbf{f}(t, \theta)$$

For instance

Nonlinear time-invariant

$$\ddot{y} + c\dot{y} + ky + \varepsilon y^3 = f(t, \theta)$$

$\varepsilon$  constant in time

Linearized time-variant

$$\ddot{x} + c\dot{x} + kx + k_{eq}(t)x = f(t, \theta)$$

$$k_{eq}(t) = 3\varepsilon\sigma_x^2(t) \text{ changes in time}$$

stationary problem  $\longrightarrow$   $k_{eq}$  time-invariant

# Equivalent linearization : example

## Gaussian Equivalent Linearization

$$\mathbf{M}\ddot{\mathbf{x}} + (\mathbf{C} + \mathbf{C}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\dot{\mathbf{x}} + (\mathbf{K} + \mathbf{K}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\mathbf{x} = \mathbf{f}(t, \theta)$$

For instance

Nonlinear time-invariant

$$\ddot{y} + c\dot{y} + ky + \varepsilon y^3 = f(t, \theta)$$

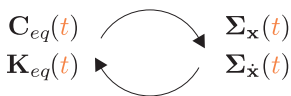
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$$\ddot{x} + c\dot{x} + kx + k_{eq}(t)x = f(t, \theta)$$

$$k_{eq}(t) = 3\varepsilon\sigma_x^2(t) \text{ changes in time}$$

Difficulty



nonlinear implicit relation

Linear Evolutionary Spectral Analysis

$$\text{LTI} \xrightarrow{?} \text{LTV}$$

in an equivalent modal basis

# Equivalent linearization : modal projection

## Gaussian Equivalent Linearization

$$\mathbf{M}\ddot{\mathbf{x}} + (\mathbf{C} + \mathbf{C}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\dot{\mathbf{x}} + (\mathbf{K} + \mathbf{K}_{eq}(\boldsymbol{\Sigma}_{\mathbf{x}}, \boldsymbol{\Sigma}_{\dot{\mathbf{x}}}))\mathbf{x} = \mathbf{f}(t, \theta)$$

Projection in a generalized basis  $\Phi$        $\mathbf{x} = \Phi \mathbf{q}$

Eigenvalue problem       $(\mathbf{K} + \tilde{\mathbf{K}})\Phi = \omega^2 \mathbf{M}\Phi$

$$\begin{array}{cc} \tilde{\mathbf{K}} = \mathbf{0} & \tilde{\mathbf{K}} \approx \mathbf{K}_{eq} \\ \text{Linear modes} & \end{array}$$

$$\ddot{\mathbf{q}} + (\mathbf{D} + \mathbf{D}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}}))\dot{\mathbf{q}} + (\boldsymbol{\Omega} + \boldsymbol{\Omega}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}}))\mathbf{q} = \mathbf{p}(t, \theta)$$

- Linear equation of motion
- Nonlinear equivalent functions

## Equivalent linearization : generalized procedure

## Equation of motion in a generalized basis

$$\ddot{\mathbf{q}} + (\mathbf{D} + \mathbf{D}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \dot{\mathbf{q}} + (\boldsymbol{\Omega} + \boldsymbol{\Omega}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \mathbf{q} = \mathbf{p}(t, \theta)$$

## Time dependent in transient dynamics

## Semi-group property

for LTI and LTV systems

$$\Psi(t, t_0) = \Psi(t, t_1)\Psi(t_1, t_0)$$



## Equation of motion in a generalized basis

$$\ddot{\mathbf{q}} + (\mathbf{D} + \mathbf{D}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \dot{\mathbf{q}} + (\boldsymbol{\Omega} + \boldsymbol{\Omega}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \mathbf{q} = \mathbf{p}(t, \theta)$$

## Time dependent in transient dynamics

## Semi-group property

for LTI and LTV systems

$t_0 \qquad t_1 \qquad t$   
 $\Psi(t, t_0) = \Psi(t, t_1)\Psi(t_1, t_0)$

## Recurrence relation

$$\Upsilon_N(t, t_0, \omega) = \Upsilon_N(t, t_1, \omega) + \Psi(t, t_1) \Upsilon_N(t_1, t_0, \omega)$$

$$\begin{aligned} \text{LTV} \quad \mathbf{h}(t) &= \int_{\mathbb{R}} \mathbf{H}(\omega) e^{j\omega t} d\omega \\ \mathbf{G}_N(t, t_1, \omega) &= \frac{\partial}{\partial t} \mathbf{G}_N(t, t_1, \omega) \end{aligned}$$

## Equivalent linearization and evolutionary analysis

Equivalent statistical linearization

Multiple scales approach

Application

# Two timescales

Equation of motion in a generalized basis

$$\frac{d^2 \mathbf{q}}{dt^2} + (\mathbf{D} + \mathbf{D}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \frac{d\mathbf{q}}{dt} + (\boldsymbol{\Omega} + \boldsymbol{\Omega}_{eq}(\boldsymbol{\Sigma}_{\mathbf{q}}, \boldsymbol{\Sigma}_{\dot{\mathbf{q}}})) \mathbf{q} = a(t) \mathbf{p}_s(t, \theta)$$

Two timescales

- **Slow time**  $t_s$  : envelope of the evolutionary process
- **Fast time**  $t_f$  : natural period of the structure

# Two timescales

Equation of motion in a generalized basis

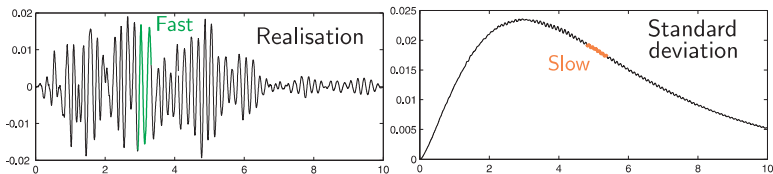
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Two timescales

- **Slow time**  $t_s$  : envelope of the evolutionary process
- **Fast time**  $t_f$  : natural period of the structure

For instance

$$\ddot{y} + c\dot{y} + ky + k_{NL}y^3 = a(t)w(t, \theta)_{\text{white noise}}$$



# Two timescales

## Two timescales

- Slow time  $t_s$  : envelope of the evolutionary process
- Fast time  $t_f$  : natural period of the structure

Flavour of demonstration

$$\left\{ \begin{array}{l} \mathbf{q}(t) \longrightarrow \mathbf{q}(t_s, t_f) \\ a(t) \longrightarrow a(t_s) \end{array} \right.$$

# Two timescales

## Two timescales

- Slow time  $t_s$  : envelope of the evolutionary process
- Fast time  $t_f$  : natural period of the structure

Flavour of demonstration  $\left\{ \begin{array}{l} \mathbf{q}(t) \longrightarrow \mathbf{q}(t_s, t_f) \\ a(t) \longrightarrow a(t_s) \end{array} \right.$

1) Statistics evolve slowly  $\Sigma_{\mathbf{q}}(t_s), \Sigma_{\dot{\mathbf{q}}}(t_s) \longrightarrow \mathbf{D}_{eq}(t_s), \Omega_{eq}(t_s)$

2)  $\frac{\partial^2 \mathbf{q}}{\partial t_f^2} + (\mathbf{D} + \mathbf{D}_{eq}(t_s)) \frac{\partial \mathbf{q}}{\partial t_f} + (\Omega + \Omega_{eq}(t_s)) \mathbf{q} = a(t_s) \mathbf{p}_s(t_s, t_f, \theta)$

# Two timescales

## Two timescales

- Slow time  $t_s$  : envelope of the evolutionary process
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$$\begin{array}{ccc} \text{LTV system} & \longrightarrow & \text{piecewise-LTI system} \\ \mathbf{D}_{eq}(t), \mathbf{\Omega}_{eq}(t) & & \mathbf{D}_{eq}(t_s), \mathbf{\Omega}_{eq}(t_s) \end{array}$$

# Generalized procedure in equivalent linearization

## Evolutionary spectral analysis

$$\hat{\mathbf{S}}_{\mathbf{z}}(t_k, \omega) = \Upsilon(t_k, t_0, \omega) \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_{\mathbf{p}} \end{bmatrix} \Upsilon(t_k, t_0, \omega)^*$$

$$\longrightarrow \Sigma_{\mathbf{z}}(t_k) = \int_{\mathbb{R}} \hat{\mathbf{S}}_{\mathbf{z}}(t_k, \omega) d\omega$$

## Recurrence relation

$$\Upsilon_{eq,N}(t_k, t_0, \omega) = \Upsilon_{eq,N}(t_k, t_{k-1}, \omega) + \Psi(t_k, t_{k-1}) \Upsilon_{eq,N}(t_{k-1}, t_0, \omega)$$



# Generalized procedure in equivalent linearization

## Evolutionary spectral analysis

$$\hat{\mathbf{S}}_{\mathbf{z}}(t_k, \omega) = \Upsilon(t_k, t_0, \omega) \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_{\mathbf{p}} \end{bmatrix} \Upsilon(t_k, t_0, \omega)^*$$

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## Recurrence relation

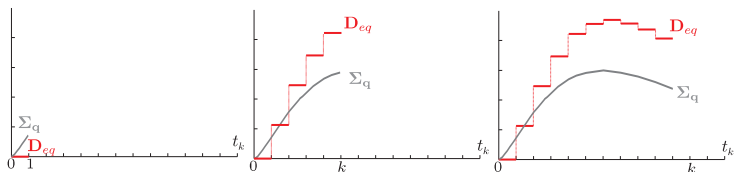
$$\Upsilon_{eq,N}(t_k, t_0, \omega) = \Upsilon_{eq,N}(t_k, t_{k-1}, \omega) + \Psi(t_k, t_{k-1}) \Upsilon_{eq,N}(t_{k-1}, t_0, \omega)$$



$$\begin{bmatrix} \mathbf{0} & \mathbf{G}_N(t_k, t_{k-1}, \omega) \\ \mathbf{0} & \partial_t \mathbf{G}_N(t_k, t_{k-1}, \omega) \end{bmatrix}$$

Asymptotic Expansion method

LTI on  $[t_{k-1}, t_k]$  with  
 $\mathbf{D}_{eq}(t_{k-1})$  and  $\mathbf{\Omega}_{eq}(t_{k-1})$



## Equivalent linearization and evolutionary analysis

Equivalent statistical linearization

Multiple scales approach

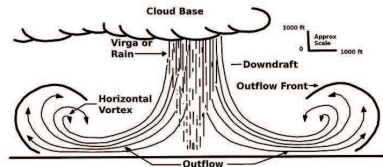
Application

# Tower subject to downburst

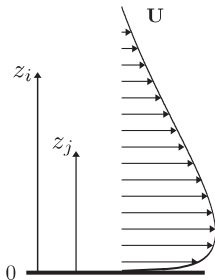
Downburst : a transient wind phenomenon

$$\mathbf{U}(t, \mathbf{z}) + \tilde{\mathbf{u}}(t, \mathbf{z})$$

mean wind      fluctuation



Mean profile

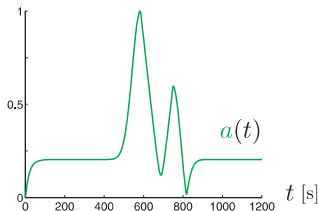


Wind psd

$$S_{\mathbf{u}}(\omega, z_i, z_j) = \sqrt{S_{\tilde{\mathbf{u}}}(\omega, z_i) S_{\tilde{\mathbf{u}}}(\omega, z_j)} \Gamma(\omega, z_i, z_j)$$

Coherence

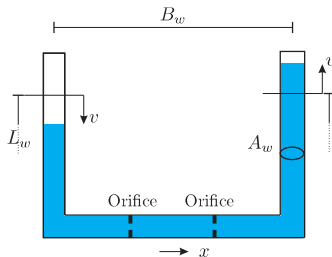
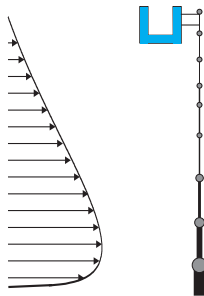
Time window



## Application

## Tower subject to downburst

Tower damped by a TLCD



$$\rho_w A_w L_w \ddot{v} + \frac{1}{2} \rho_w A_w \delta |\dot{v}| \dot{v} + 2 \rho_w A_w g v = -\rho_w A_w B_w \ddot{x}$$

Equivalent linearization

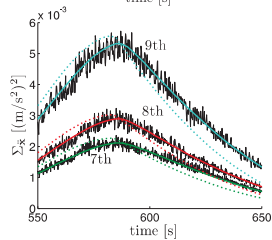
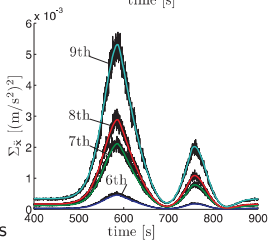
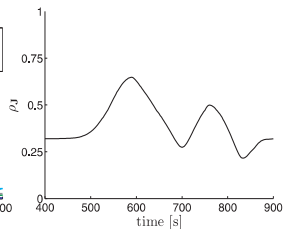
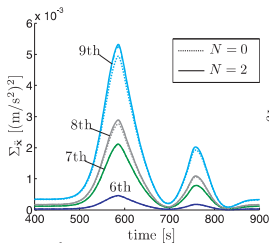
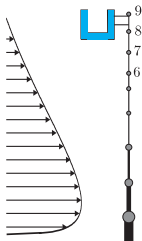
$$\rho_w A_w L_w \ddot{v} + \sqrt{\frac{2}{\pi}} \rho_w A_w \delta \sigma_{\dot{v}} \dot{v} + 2 \rho_w A_w g v = -\rho_w A_w B_w \ddot{x}$$

# Tower subject to downburst

## Multiple scales approach

Natural frequency : 0.23 Hz

Time window :  $\Delta t = 10\text{s}$



MC: 1000 samples

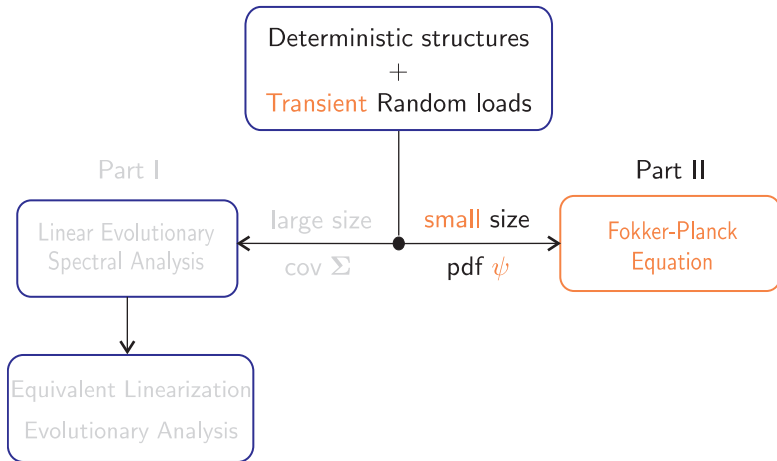
# Conclusions

## Goals

- Develop an efficient method for linear evolutionary spectral analysis
- Ability to deal with coherent random loads
- Extend this method to Gaussian equivalent linearization

## Achievements

- Asymptotic expansions of  $\mathbf{H}(\omega)$ ,  $\mathbf{h}(t)$  and  $\mathbf{G}(t, \omega)$
- Convergence criteria in frequency and time (improvements)
- Recurrence relation to compute  $\Upsilon(t, t_0, \omega)$  in a state space formalism
- Extension to equivalent linearization with a multiple scales approach
- Application in wind engineering : tower subject to downburst



## Purpose and motivations

## Fokker-Planck-Kolmogorov equation

Purpose and motivations

Smoothed Particle Hydrodynamics Method

FPK with SPH

Applications



## Purpose and motivations

# Fokker-Planck-Kolmogorov Equation

## Equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = \mathbf{a}(t)\mathbf{w}(t)$$



$$\dot{\mathbf{z}}(t, \theta) = \mathbf{f}(t, \mathbf{z}) + \mathbf{b}(t, \mathbf{z})\mathbf{W}(t)$$

## Purpose and motivations

## Fokker-Planck-Kolmogorov Equation

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$$\dot{\mathbf{z}}(t, \theta) = \mathbf{f}(t, \mathbf{z}) + \mathbf{b}(t, \mathbf{z})\mathbf{W}(t)$$

## FPK equation



$$\frac{\partial \psi}{\partial t} + \sum_{i=1}^n \underbrace{\frac{\partial}{\partial z_i} (f_i \psi)}_{\text{convection}} = \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial z_i \partial z_j} (D_{ij} \psi) \quad \text{diffusion}$$

transport and conservation of the pdf  $\psi(t, \mathbf{z})$

## Purpose and motivations

## Fokker-Planck-Kolmogorov Equation

## Equation of motion

$$\mathbf{M}\ddot{\mathbf{y}} + \mathbf{C}\dot{\mathbf{y}} + \mathbf{K}\mathbf{y} + \mathbf{g}(\mathbf{y}, \dot{\mathbf{y}}) = a(t)\mathbf{w}(t)$$



$$\dot{\mathbf{z}}(t, \theta) = \mathbf{f}(t, \mathbf{z}) + \mathbf{b}(t, \mathbf{z})\mathbf{W}(t)$$

## FPK equation



$$\frac{\partial \psi}{\partial t} + \underbrace{\sum_{i=1}^n \frac{\partial}{\partial z_i} (f_i \psi)}_{\text{convection}} = \underbrace{\sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial z_i \partial z_j} (D_{ij} \psi)}_{\text{diffusion}}$$

transport and conservation of the pdf  $\psi(t, \mathbf{z})$

## Complementary conditions

$$\psi_0(\mathbf{z})$$

initial distribution

$$\int_{\mathbb{R}} \psi(t, \mathbf{z}) d\mathbf{z} = 1$$

conservation

$$\psi(t, \mathbf{z}) > 0$$

positivity

# Motivations

## Goal of this part

- solve **numerically** FPK equation
- for **nonlinear** systems and **transient** excitations
- apply to extreme value problems, **tails** of pdf

## Which conditions must fulfill the FPK solver ?

- ensure the **positivity** and the **conservation**
- **stability** in the transient phase
- be able to deal with **slightly to highly** dispersed distributions
- extendable to **high-dimensional** systems

## Method

## Smoothed Particle Hydrodynamics

probability = hypothetical fluid

## Fokker-Planck-Kolmogorov equation

Purpose and motivations

Smoothed Particle Hydrodynamics Method

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Applications

# Generalities about SPH Method

- Meshless method

Particles are integration points

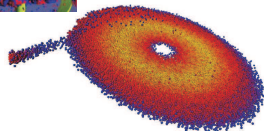
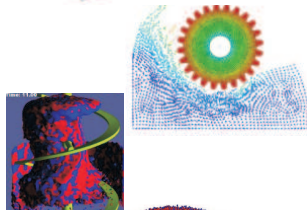
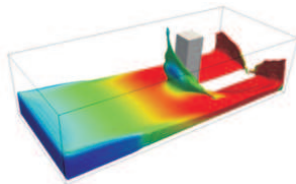
- Lagrangian formalism

Point of view of a non-fixed observator

- Integral representation of a field  $\phi(\mathbf{x})$

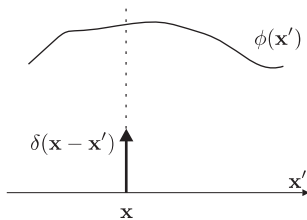
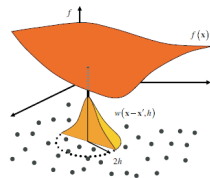
$$\phi(\mathbf{x}) = \int_{\mathbb{R}^n} \phi(\mathbf{x}') \delta(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$

$\delta(\cdot)$  a delta-Dirac function

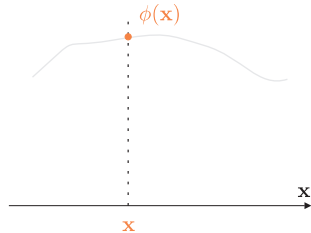


## Integral representation of a field

$$\phi(\mathbf{x}) = \int_{\mathbb{R}^n} \phi(\mathbf{x}') \delta(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$



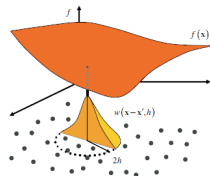
$$\int_{\mathbb{R}^n}$$



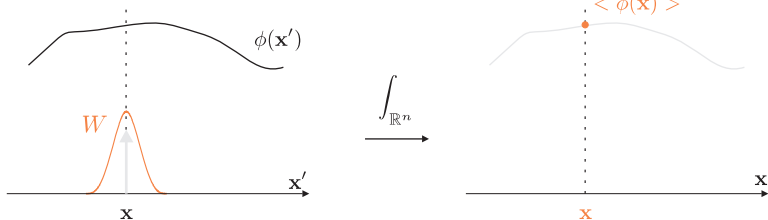
## Integral representation of a field

$$\phi(\mathbf{x}) = \int_{\mathbb{R}^n} \phi(\mathbf{x}') \delta(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$

$$\langle \phi(\mathbf{x}) \rangle = \int_{\mathbb{R}^n} \phi(\mathbf{x}') W(|\mathbf{x} - \mathbf{x}'|, h) d\mathbf{x}'$$



with  $W(., h)$  the **kernel function** and  $h$  the **smoothing length**

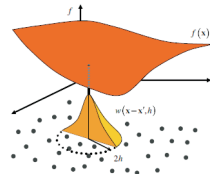




## Integral representation of a field

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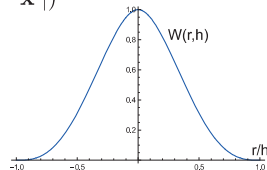
## Kernel Function

**$\delta$ -Dirac property**  $\lim_{h \rightarrow 0} W(|\mathbf{x} - \mathbf{x}'|, h) = \delta(|\mathbf{x} - \mathbf{x}'|)$

**unity**  $\int_{\mathbb{R}^n} W(|\mathbf{x} - \mathbf{x}'|, h) d\mathbf{x}' = 1$

compact support, monotonic decay

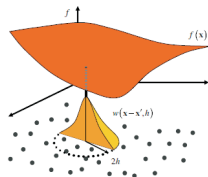
symmetry, positivity and smoothness



## Integral representation of a field

$$\phi(\mathbf{x}) = \int_{\mathbb{R}^n} \phi(\mathbf{x}') \delta(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$

$$\langle \phi(\mathbf{x}) \rangle = \int_{\mathbb{R}^n} \phi(\mathbf{x}') W(|\mathbf{x} - \mathbf{x}'|, h) d\mathbf{x}'$$



with  $W(., h)$  the kernel function and  $h$  the smoothing length

## Discretization of the integral

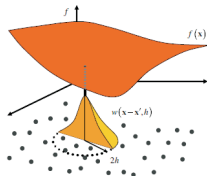
$$\langle \phi(\mathbf{x}) \rangle \approx \sum_{j=1}^{N_p} \phi(\mathbf{x}_j) W(|\mathbf{x} - \mathbf{x}_j|, h) \Delta V_j$$

number of particles
volume of particle  $j$

## Integral representation of a field

$$\phi(\mathbf{x}) = \int_{\mathbb{R}^n} \phi(\mathbf{x}') \delta(\mathbf{x} - \mathbf{x}') d\mathbf{x}'$$

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$$\langle \phi(\mathbf{x}) \rangle \approx \sum_{j=1}^{N_p} \phi(\mathbf{x}_j) W(|\mathbf{x} - \mathbf{x}_j|, h) \Delta V_j$$

$N_p$  ← number of particles  
 $\Delta V_j$  ← volume of particle  $j$

## Discretization of the kernel approximation

$$\langle \phi(\mathbf{x}_i) \rangle = \sum_{j=1}^{N_p} \phi(\mathbf{x}_j) W(|\mathbf{x}_i - \mathbf{x}_j|, h) \Delta V_j$$

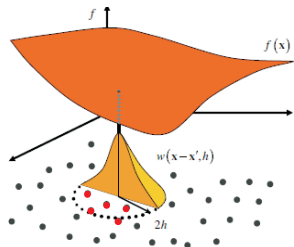
# Particle Interaction

## Kernel approximation

$$\langle \phi(\mathbf{x}_i) \rangle = \sum_{j=1}^{N_p} \phi(\mathbf{x}_j) W(|\mathbf{x}_i - \mathbf{x}_j|, h) \Delta V_j$$

A particle  $i$  interacts with all the particles  
within its compact support

How to compute the interaction ?

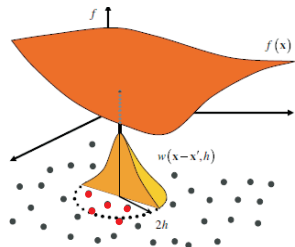


# Particle Interaction

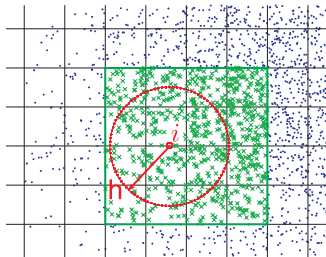
## Kernel approximation

$$\langle \phi(\mathbf{x}_i) \rangle = \sum_{j=1}^{N_p} \phi(\mathbf{x}_j) W(|\mathbf{x}_i - \mathbf{x}_j|, h) \Delta V_j$$

A particle  $i$  interacts with all the particles  
within its compact support



## How to compute the interaction ?



1. The state space is divided into *cells*
2. The particles are sorted in these *cells*
3. For a particle  $i$ , a set of cells including its compact support is found
4.  $\langle \phi_i \rangle$  is built with particles contained in these cells

## Fokker-Planck-Kolmogorov equation

Purpose and motivations

Smoothed Particle Hydrodynamics Method

**FPK with SPH**

Applications

# Lagrangian Paradigm

## Eulerian formalism of conservation equation

$$\frac{\partial \psi}{\partial t} + \sum_{i=1}^n \frac{\partial}{\partial z_i} \left( f_i \psi - \sum_{j=1}^n \frac{\partial}{\partial z_j} (D_{ij} \psi) \right) = 0$$

$$\left\{ \begin{array}{l} \frac{\partial \psi}{\partial t} + \nabla \cdot (\mathbf{v} \psi) = 0 \quad \text{with} \quad v_i = f_i - \sum_{j=1}^n \frac{\partial D_{ij}}{\partial z_j} - \sum_{j=1}^n D_{ij} \frac{1}{\psi} \frac{\partial \psi}{\partial z_j} \end{array} \right.$$

Particle velocity : convection and diffusion effects

# Lagrangian Paradigm

## Eulerian formalism of conservation equation

$$\frac{\partial \psi}{\partial t} + \sum_{i=1}^n \frac{\partial}{\partial z_i} \left( f_i \psi - \sum_{j=1}^n \frac{\partial}{\partial z_j} (D_{ij} \psi) \right) = 0$$

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Particle velocity : convection and diffusion effects

## Lagrangian formalism      particles = non-fixed observators

conservation of the total probability       $\frac{D\psi}{Dt} + \psi \nabla \cdot \mathbf{v} = 0$

material  
derivative

transport equation for particles

$$\mathbf{v} = \frac{d\mathbf{X}}{dt}$$

particle  
position



# Lagrangian Paradigm

## Eulerian formalism of conservation equation

$$\frac{\partial \psi}{\partial t} + \sum_{i=1}^n \frac{\partial}{\partial z_i} \left( f_i \psi - \sum_{j=1}^n \frac{\partial}{\partial z_j} (D_{ij} \psi) \right) = 0$$

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Particle velocity : convection and diffusion effects

## Lagrangian formalism      particles = non-fixed observators

conservation of the total probability       $\frac{D\psi}{Dt} + \psi \nabla \cdot \mathbf{v} = 0$       material derivative

transport equation for particles       $\mathbf{v} = \frac{d\mathbf{X}}{dt}$       particle position

# Conservation equation

The conservation equation of probability is similar  
to the conservation of mass in the [Navier-Stokes equation](#)

$$\frac{D\psi}{Dt} + \psi \nabla \cdot \mathbf{v} = 0$$

we don't solve this equation

With SPH method,  $\psi$  is a [scalar field](#) that can be approximated by

$$\langle \psi(\mathbf{x}_i) \rangle = \sum_{j=1}^{N_p} \psi_j W_{ij} \Delta V_j = \sum_{j=1}^{N_p} \mu_j W_{ij}$$

# Conservation equation

The conservation equation of probability is similar  
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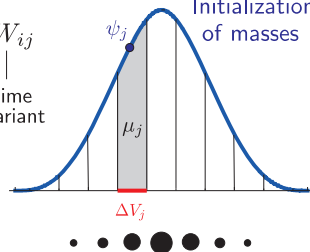
$$\frac{D\psi}{Dt} + \psi \nabla \cdot \mathbf{v} = 0$$

we don't solve this equation

With SPH method,  $\psi$  is a **scalar field** that can be approximated by

$$\langle \psi(\mathbf{x}_i) \rangle_{\text{time variant}} = \sum_{j=1}^{N_p} \psi_j W_{ij} \Delta V_j = \sum_{j=1}^{N_p} \underbrace{\mu_j}_{\text{time variant}} \underbrace{W_{ij}}_{\text{constant "mass"}}$$

Initialization  
of masses



## Advantages

- The positivity of the pdf is ensured
- The total probability is conserved
- No differential, nor algebraic equation, is solved

# Transport equation

A particle  $i$  at a position  $\mathbf{X}_i$  has a velocity  $\mathbf{v}_i$  given by

$$\mathbf{v}_i = \underbrace{\mathbf{f}(\mathbf{X}_i)}_{\text{convection}} - \mathbf{D} \frac{\underbrace{\langle \nabla \psi(\mathbf{X}_i) \rangle}_{\text{diffusion}}}{\underbrace{\langle \psi(\mathbf{X}_i) \rangle}_{\text{diffusion}}}$$

gradient of the probability field

Transport equation of particle  $i$

$$\frac{d\mathbf{X}_i}{dt} = \mathbf{v}_i \quad \longrightarrow \quad \underbrace{\mathbf{X}_i^{t+\Delta t}}_{\text{new position}} = \mathbf{X}_i^t + \mathbf{v}_i \Delta t$$

Resolution scheme

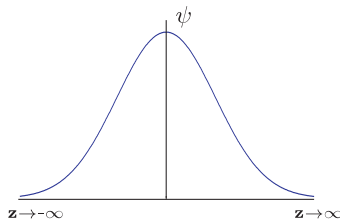
$$\mathbf{X}_i^t \longrightarrow r_{ij} \longrightarrow W_{ij} \longrightarrow \langle \psi_i^t \rangle \longrightarrow \mathbf{v}_i^t \longrightarrow \mathbf{X}_i^{t+\Delta t}$$

# Boundary conditions

## Vanishing condition in the far-field

$$\lim_{\|\mathbf{z}\| \rightarrow \infty} \psi(t, \mathbf{z}) \rightarrow 0, \quad \forall t \in \mathbb{R}^+$$

- No need for specific treatment
- Presence of low mass particles
- Instability in mesh-based methods



## Other boundary conditions

Absorbing condition

Periodic condition

## Fokker-Planck-Kolmogorov equation

Purpose and motivations

Smoothed Particle Hydrodynamics Method

FPK with SPH

Applications

# Hysteretic Oscillator

## Elastoplastic oscillator in 3D

$$\text{Bouc-Wen model} \quad \left\{ \begin{array}{l} \ddot{q} + 2\xi\omega_0\dot{q} + \Phi = aW \\ \Phi = \omega_0^2 (\alpha q + (1 - \alpha)z) \\ \dot{z} = \dot{q} (A - (\beta \text{sign}(\dot{q}z) + \gamma) |z|^n) \end{array} \right.$$

## SPH solution

- SPH-FPK : 9261 particles
- Transience :  $a$  time window
- Simplification :  $W$  white noise
- $n = 1$ , hist.variable  $z$  is bounded
- At  $t_0$ , particles are regularly spread
- Initial condition *quasi*-deterministic

# Reliability problems

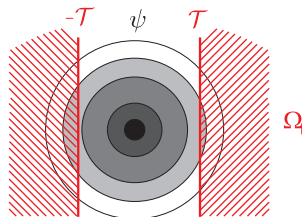
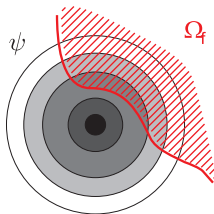
## Probability of exceedance

The mathematical formulation of a reliability problem consists in calculating the probability of exceedance  $P_f$  to be in  $\Omega_f$  the subspace of failure

$$P_f(t) = \int_{\Omega_f} \psi(t, \mathbf{x}) d\mathbf{x} \quad \longrightarrow \quad \langle P_f(t) \rangle = \sum_{j=1}^{N_p} \mu_j \mathbb{I}(\mathbf{X}_j(t) \in \Omega_f)$$

sum of the masses of  
the particles within  $\Omega_f$

For instance





# Hysteretic Oscillator

## Elastoplastic oscillator in 3D

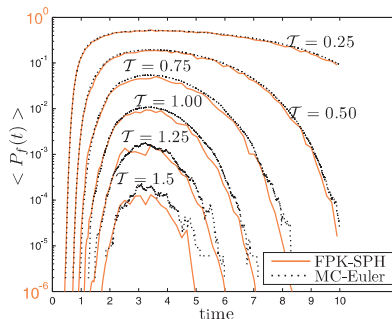
$$\text{Bouc-Wen model} \quad \left\{ \begin{array}{l} \ddot{q} + 2\xi\omega_0\dot{q} + \Phi = aW \\ \Phi = \omega_0^2 (\alpha q + (1-\alpha)z) \\ \dot{z} = \dot{q} (A - (\beta \text{sign}(\dot{q}z) + \gamma) |z|^n) \end{array} \right.$$

## Reliability problem

$$\Omega_{\mathcal{T}} = \{[q \dot{q} z] \in \mathbb{R}^3; |q| > \mathcal{T} > 0\}$$

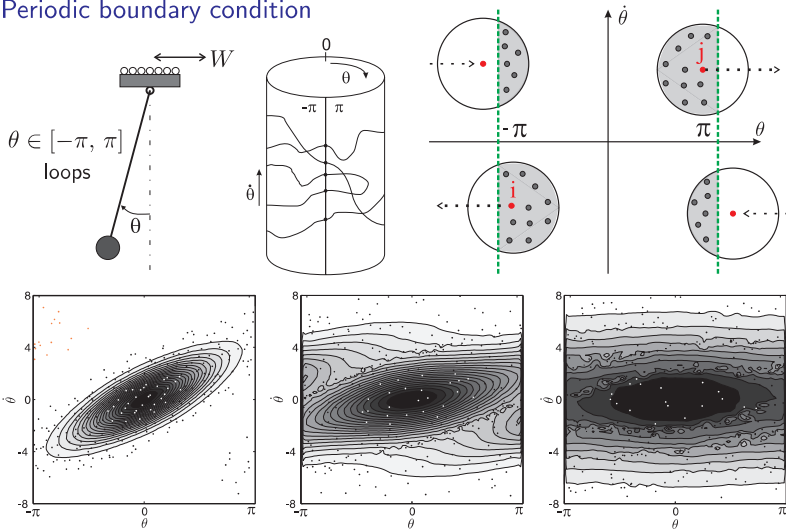
with  $\mathcal{T}$  a threshold

- SPH-FPK : 9261 particles
- Monte-Carlo :  $5 \cdot 10^5$  samples
- 6 orders of magnitude are covered
- Time evolution well estimated



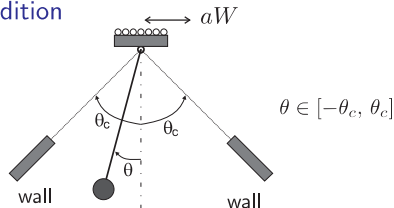
# Randomly excited pendulum

Periodic boundary condition

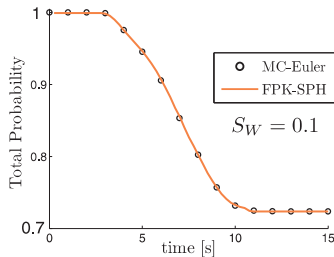
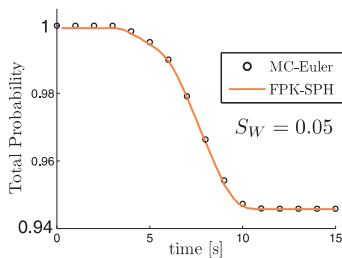


# Randomly excited pendulum

## Absorbing boundary condition



Probability at  $t$  to not have hit the wall ?



# Conclusions

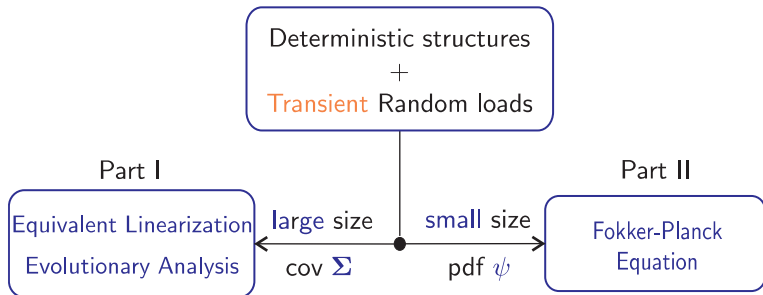
## Main advantages of SPH method

- The positivity of the pdf is ensured
- There is no particular treatment for vanishing conditions
- The formalism is easily extended to high-dimension systems
- No algebraic equation is solved

## Some limitations

- The stationary distribution cannot be directly computed
- The computation of interactions for large number of particles to improve

# Summary



1. Asymptotic expansion method
2. Efficient generalized procedure
3. Multiple timescales approach

1. Smoothed Particle Hydrodynamics
2. Eulerian vs Lagrangian formalisms
3. Probability of exceedance